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MEASUREMENT CORRELATION FOR MULTIPLE SENSOR TRACKING IN A DENSE--ETC(U)
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Technical Report 549

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Measurement Correlation for Multiple Sensor Tracking in a Dense Target Environment

20 January 1981

Prepared for the Department of the Army under Electronic Systems Division Contract F19628-80-C-0002 by

Lincoln Laboratory

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

LEXINGTON, MASSACHUSETTS

Approved for public release; distribution unlimited.

The work reported in this document was performed at Lincoln Laboratory, a center for research operated by Massachusetts Institute of Technology. This program is sponsored by the Ballistic Missile Defense Program Office, Department of the Army; it is supported by the Ballistic Missile Defense Advanced Technology Center under Air Force Contract F19628-80-C-0002.

This technical report has been reviewed and is approved for publication.

FOR THE COMMANDER

Raymond L. Loiselle

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MASSACHUSETTS INSTITUTE OF TECHNOLOGY

LINCOLN LABORATORY

MEASUREMENT CORRELATION FOR MULTIPLE SENSOR TRACKING IN A DENSE TARGET ENVIRONMENT

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Group 32

TECHNICAL REPORT 549

20 JANUARY 1981

LEXINGTON MASSACHUSETTS

ABSTRACT

In this report, we describe an algorithm for correlating measurements from several sensors. This is a problem area in multiple sensor tracking in a dense target environment. It is shown that the correlation problem is similar to the assignment problem in operation research with assignment penalties being equal to the sufficient statistic of the generalized likelihood ratio test. An example is given to illustrate the correlation performance for two optical sensors tracking ballistic trajectories.

CONTENTS

1. INTRODUCTION

In many target tracking applications, one is confronted with the problem of multiple sensors simultaneously tracking a number of targets. This situation brings up at least three problem areas: (1) the identification of a time sequence of measurements associated with the same target, (2) the identification of measurements from several sensors associated with the same target, and (3) efficient algorithms for processing multiple sensor data after both (1) and (2) have been completed.

The first problem above is often referred to as the problem of multiobject tracking and has received considerable attention in recent years*. The second problem can be viewed as a special case of the first; it does have, however, its own characteristics and can be treated separately. This is the subject of this report. The problem (3) above was the subject of Ref. [3] where Kalman filter configurations for multiple sensor data processing were studied in detail.

In this report, we present an algorithm for identifying the same object from measurements made by several sensors. It can be shown that the sensor to sensor measurement correlation problem is the same as the classical assignment problem in operation research, [4]-[5]. The penalties or performance

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*See Refs. [1] and [2] for a survey of open literatures.

ratings used for association can be shown to be the sufficient statistic of the multiple hypothesis generalized likelihood ratio test. For Gaussian random vectors, the sufficient statistic follows the chi-square distribution. This property can be used to eliminate those measurements which are highly unlikely to be correlated with the same target. All these derivations will be shown in the next section. In the third section, we give an example showing the performance of correlating measurements of two optical sensors tracking multiple ballistic targets.

2. A CORRELATION ALGORITHM

2.1. The Generalized Likelihood Ratio Test

Let $\underline{y}_{ij}$ denote the j-th measurement of the i-th sensor, assuming that there are M sensors taking measurements on the same N targets. The problem where the target sets observed by each sensor are not identical will be discussed later.

We note that the term "measurement" should be interpreted in a more general sense. For example, $\underline{y}_{ij}$ may represent a state estimate of the j-th target from the i-th sensor. In another example, a subset of $\underline{y}_{ij}$ may be actual measurements and the remaining subset are predicted measurements from target state estimators. This second case is the same as the track maintenance problem of multiple sensor tracking in a dense target environment.

We assume that all $\underline{y}_{ij}$'s are in the same coordinate system. For a specific application, the required transformation for satisfying the above assumption can be defined.

Let H_k denote the hypothesis that the same target has generated measurements $\{\underline{y}_{ij_i};\ i=1,\ldots,M\}$. There are therefore a total of N^M possible hypotheses. Let $\underline{x}$ denote the true measurement vector corresponding to H_k then the generalized likelihood ratio test requires the following decision function [6]

$$d(\underline{y}_{ij_i};\ i=1,\ldots,M) \tag{2.1}$$

where the above decision function is obtained by using the maximum likelihood estimate of $\underline{x}$, i.e., the $\hat{\underline{x}}$ satisfying

$$\max_{\underline{x}} \left(p(\underline{y}_{ij_i};\ i=1,\ldots,M/x)\right) \tag{2.2}$$

Substituting $\hat{\underline{x}}$ in the density $p(\underline{y}_{ij_i};\ i=1,\ldots,M/\underline{x})$ gives the decision function (2.1). Equations (2.1) and (2.2) form the sufficient statistic for correlating measurements from multiple sensors.

If the measurement noise vector is independent between sensors and follows a Gaussian density function with zero mean and covariance P_{ij}, then equation (2.1) becomes

$$d(\underline{y}_{ij_i};\ i=1,\ldots,M) = c\ \exp\left\{-1/2 \sum_{i=1}^{M} (\underline{y}_{ij_i} - \hat{\underline{x}})^T P_{ij_i}^{-1} (\underline{y}_{ij_i} - \hat{\underline{x}})\right\} \tag{2.3}$$

where

$$\hat{\underline{x}} = \left[\sum_{i=1}^{M} P_{ij_i}^{-1}\right]^{-1} \left[\sum_{i=1}^{M} P_{ij_i}^{-1} \underline{y}_{ij_i}\right] \tag{2.4}$$

Notice that the $\hat{\underline{x}}$ above is the maximum likelihood estimate of $\underline{x}$ assuming that all $\underline{y}_{ij_i}$'s are correlated. When this is true, it is the <u>compressed</u> measurement discussed in [3]. Equations (2.3)-(2.4) give the sufficient statistic for the Gaussian measurement noise case.

In order to further illustrate the above results, let us consider the problem of correlating measurements from two sensors. Let $\{\underline{y}_i,\ i=1,\ldots,N\}$ and $\{\underline{z}_j,\ j=1,\ldots,N\}$ denote the measurements of the first and second sensors, respectively. Furthermore, we assume that the measurement noise vectors of $\underline{y}_i$ and $\underline{z}_j$ are Gaussian with zero mean and covariance P_i and Σ_j, respectively. Using these assumptions, then Eq. (2.3) becomes

$$d(\underline{y}_i,\underline{z}_j) = c\ \exp\{-1/2[(\underline{y}_i-\underline{\hat{x}})^T P_i^{-1}(\underline{y}_i-\underline{\hat{x}})+(\underline{z}_j-\underline{\hat{x}})^T\Sigma_j^{-1}(\underline{z}_j-\underline{\hat{x}})]\} \tag{2.5}$$

where

$$\underline{\hat{x}} = [P_i^{-1}+\Sigma_j^{-1}]^{-1}[P_i^{-1}\underline{y}_i+\Sigma_j^{-1}\underline{z}_j] \tag{2.6}$$

One can now simplify Eq. (2.5) by substituting (2.6) in (2.5). This is done with the following derivations:

(1) $\underline{y}_i-\underline{\hat{x}}$

$$= \{I-[P_i^{-1}+\Sigma_j^{-1}]^{-1}P_i^{-1}\}\underline{y}_i-[P_i^{-1}+\Sigma_j^{-1}]^{-1}\Sigma_j^{-1}\underline{z}_j$$

$$= [P_i^{-1}+\Sigma_j^{-1}]^{-1}(\Sigma_j^{-1}\underline{y}_i-\Sigma_j^{-1}\underline{z}_j)$$

$$= [\Sigma_j P_i^{-1}+I]^{-1}(\underline{y}_i-\underline{z}_j)$$

(2) $(\underline{y}_i-\underline{\hat{x}})^T P_i^{-1}(\underline{y}_i-\underline{\hat{x}})$

$$= (\underline{y}_i-\underline{z}_j)^T[\Sigma_j+P_i]^{-1}P_i[\Sigma_j+P_i]^{-1}(\underline{y}_i-\underline{z}_j) \tag{2.7}$$

(3) Similarly, one obtains

$$\underline{z}_j-\underline{\hat{x}} = [P_i\Sigma_j^{-1}+I]^{-1}(\underline{y}_i-\underline{z}_j)$$

$$(z_j-\underline{\hat{x}})^T\Sigma_j^{-1}(\underline{z}_j-\underline{\hat{x}})$$

$$= (\underline{y}_i-\underline{z}_j)^T[P_i+\Sigma_j]^{-1}\Sigma_j[P_i+\Sigma_j]^{-1}(\underline{y}_i-\underline{z}_j) \tag{2.8}$$

Substituting (2.7) and (2.8) into (2.5) yields

$$d(\underline{y}_i, \underline{z}_j)$$

$$= C \exp\{-1/2(\underline{y}_i-\underline{z}_j)^T[P_i+\Sigma_j]^{-1}(\underline{y}_i-\underline{z}_j)\} \quad (2.9)$$

Notice that all information for decision is contained in the exponent of $d(\underline{y}_i, \underline{z}_j)$. It is therefore the sufficient statistic for the generalized likelihood ratio test, i.e.,

$$\ell_{ij} = (\underline{y}_i-\underline{z}_j)^T[P_i+\Sigma_j]^{-1}(\underline{y}_i-\underline{z}_j) \quad (2.10)$$

Notice that ℓ_{ij} can be interpreted as a weighted distance measure between $\underline{y}_i$ and $\underline{z}_j$. For the case that $\underline{y}_i$ and $\underline{z}_j$ are indeed from the same target, ℓ_{ij} follows a chi-square distribution. For the case that the above situation is not true, $\underline{y}_i-\underline{z}_j$ is not zero mean, ℓ_{ij} therefore has high probability of attaining values larger than that of a chi-square random variable. This fact forms the basis of using chi-square statistics for choosing a threshold for pre-screening ℓ_{ij}'s.

Consider the case that one would like to decide which $\underline{y}_i$ is correlated with a particular $\underline{z}_j$. For a fixed j, the generalized multiple hypothesis testing procedure will select the $\underline{y}_i$ satisfying

$$\min_{i=1,\ldots,N} \ell_{ij} \quad ; \text{ for a given } j. \quad (2.11)$$

If one simply repeats the above procedure for all j, then ambiguous situations may arise. This is because the same measurement of a given sensor may be selected as correlated with several measurements of the other sensor while some measurements may be declared uncorrelated completely. This situation may be possible when sensors do not have perfect resolution, e.g., a sensor may report only one measurement for several closely spaced targets while the second sensor has already resolved these targets. Situations like this can be treated by considering the property of the Chi-square distribution and this subject will be discussed in Section 2.3. For the case that unambiguous matches between $\underline{y}_i$ and $\underline{z}_j$ must be made (i.e., the completely resolved case), this gives rise to the classical assignment problem.

2.2. The Assignment Problem

Consider Table 2.1. Entries of the matrix can be ℓ_{ij}'s of Eq. (2.10). In the classical assignment problem of operations research, the ℓ_{ij} may represent the penalty (or payoff) of assigning the i-th person to work on the j-th job. The optimum assignment is selected as these entries giving

$$\min_{i,j} \sum_{i,j} \ell_{ij} \tag{2.12}$$

with the constraint that each column/row can be assigned to a row/column only once.

TABLE 2.1

ENTRIES OF AN ASSIGNMENT PROBLEM

Measurements of 1st Sensor

Measurements of 2nd Sensor

	$\underline{y}_1$	$\underline{y}_2$	$\underline{y}_3$	.	.	.	$\underline{y}_N$
$\underline{z}_1$	ℓ_{11}	ℓ_{12}	ℓ_{13}	.	.	.	ℓ_{1N}
$\underline{z}_2$	ℓ_{21}	ℓ_{22}	ℓ_{23}	.	.	.	ℓ_{2N}
$\underline{z}_3$	ℓ_{31} .	.	.	.	.	.	.
.	.						
.	.						
.	.						
.	.						
$\underline{z}_N$	ℓ_{N1} .	.	.	.	.	.	ℓ_{NN}

ℓ_{ij} = the sufficient statistic of assuming $\underline{z}_i$ and $\underline{y}_j$ being correlated.

Notice that the above matrix is similar to the threat distribution matrix discussed in [8] except that the threat/target correlation does not have the unique match constraint.

A trivial approach to the above optimization problem is to enumerate all possible combinations and choose the one with minimum sum. This results in N! trials. A classical method called the Hungarian algorithm [4] which requires substantially fewer operations has been known for many years in the field of combinatorial programming. A particular method of implementing the Hungarian algorithm given by Munkre [5]* requires at most $(11N^3+12N^2+31N)/6$ operations representing a substantial saving for large N's. The details of the Hungarian/Munkre algorithm will not be repeated here.

There is a "suboptimal" approach to the assignment problem called the row and column elimination method. This algorithm proceeds as follows.

(1) select an arbitrary row (or column), find its minimum entry,

(2) search the corresponding column (or row) containing this entry for a minimum.

(3) repeat (1) and (2) until this entry is the minimum for both the row and the column containing it. This row and column are declared to be correlated.

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*The authors are indebted to Dr. R. B. Holmes for pointing out this reference.

(4) eliminate this row and column from further consideration, then repeat (1)-(3) until all rows and columns have been eliminated.

The above algorithm is "suboptimal" because it does not always give optimal solution for (2.12). In the sensor-to-sensor correlation problem, if the target density is sufficiently "low" such that a ℓ_{ij} which does not correspond to the same target will attain a much larger value, then the row and column elimination method frequently gives the optimum solution.

The above discussions illustrate the problem of correlating measurements from <u>two</u> sensors. For more than two sensors, the computational load increases rapidly although the problem is conceptually straightforward. In a multiple sensor problem, one first computes the sufficient statistic using (2.1)-(2.2). Let it be denoted as $\ell_{i_1,i_2,i_3,\ldots,i_M}$ where M is the total number of sensors. One can now visualize the $\ell_{i_1,\ldots,i_M}$ as entries of a "super matrix" with dimension (N x N x N x...x N) where there are M N's. The correlation solution is given by the combination of mutually independent entries achieving the minimum sum. It is interesting to note that a corresponding Hungarian/Munkre algorithm for the aforementioned problem does not seem to be available yet. An exhaustive search method will require enumerating $(N!)^{M-1}$ possiblities and this number looks prohibitive even for a modest range of N and M. The computational requirement for the row and column elimination method is still reasonable but this method works well only for a modest target density.

Finally, we comment that the solution criterion given by (2.12) represents one of many possibilities. A more general performance index can be chosen as

$$J = \begin{cases} \sum_{i,j} |\ell_{i,j}|^p , \quad \text{for } p \geq 1 & (2.13) \\ \\ \max_{i,j} \ell_{i,j} & (2.14) \end{cases}$$

Notice that the above criterion corresponds to the minimum norm problem in Banach space. If one chooses (2.14) as the criterion for minimization, this corresponds to the minimum maximum entry problem. The criterion (2.12) chosen for this report corresponds to a minimum error probability.

2.3. The Chi-Square Thresholding Technique

The discussion in the above two sections constitutes an essential portion of a sensor-to-sensor correlation algorithm. It does not however, consider situations when (1) sensor field of views (FOV) do not completely overlap and (2) the sensor resolution capability is limited. For these situations, we consider an approach based upon the Chi-square statistics.

As we noted earlier for the Gaussian measurement noise case, if ℓ_{ij} is formed by the same target, it is a Chi-square random variable. A Chi-square random variable x with n-th degree-of-freedom follows the following density function [7]:

$$p(x) = \frac{A}{2(2\pi)^{n/2}\sigma^n \bar{x}} x^{(n-1)/2} e^{-x/2\sigma^2} \qquad (2.15)$$

where A is a normalization factor. With (2.15) one can compute the cumulative probability of x.

When ℓ_{ij} is formed by two different targets, then $\underline{y}_i - \underline{z}_j$ has a non-zero mean. For this case the ℓ_{ij} is proportional to the square of the mean vector, it will therefore attain a value larger than that of a Chi-square variable. When one forms the ℓ_{ij} matrix (Table 2.1), one can first disqualify those large ℓ_{ij}'s because they are statistically unlikely to be correlated. This procedure will result in a partially filled matrix. Some parts of the matrix may become disjoint from the others. Their minimum solutions are independent of the rest, they can therefore be treated independently. Resolving several smaller matrices is computationally more efficient than resolving one larger matrix. Some of the submatrices may not be square and may not be completely filled. The Hungarian/Munkre method can be trivially modified to handle this case.

A target which appears only in the FOV of one sensor will result in large ℓ_{ij} values, and will therefore likely be discarded in the above thresholding process.

When target density is high so that some sensors may not be able to resolve some closely space targets, the ℓ_{ij} values will be small even for mismatched cases. In order to reduce the probability of leakage, one may want to accept one measurement of one sensor to be correlated with several measurements of the other sensor. For examples, let ℓ_{ij} denote the i-th measurement from the first sensor and j-th measurement from the second sensor which have been declared correlated using the method of Section 2.2. One then searches for those entries of i-th row and j-th column which are within a certain value of ℓ_{ij}. All these entries will be accepted as possible correlations. This method will increase the correct correlation rate for the case with imperfect sensor resolution and high target density, it will nevertheless also increase the false alarm rate. A later numerical example will illustrate this fact.

The above discussion establishes a method for rejecting highly unlikely correlations and for accepting multiple correlations. This method may be ad hoc but an exact approach seems to be difficult to obtain.

We note that for the case of more than two sensors, the sufficient statistic for Gaussian measurement noise case is also a Chi-square random variable and the discussions above also apply. There may be cases such that a target appears in some sensors and does not appear in others. Such a target may also obtain a small sufficient statistic when it is computed with a nearby target. This is because the sufficient statistic (Eqs. (2.3)-(2.4)) is obtained as the averaged weighted distance. To circumvent this problem, one may first want to perform correlation tests for all two-sensor pairs and isolate those targets which do not appear in all sensors. Those targets which are identified to be common to the same sensors will be processed together.

2.4. Algorithm Summary

We now summarize the above discussions to give an algorithm for multiple sensor measurement correlation.

(1) Choose two sensors, compute the sufficient statistic, ℓ_{ij}, between their measurements using (2.1)-(2.2), or (2.9) for the Gaussian measurement noise case.

(2) For a desired leakage probability, a threshold can be chosen using (2.15). Apply the threshold to eliminate those measurements which are unlikely to be correlated. Identify those targets which appear to only one sensor.

(3) Repeat (1) and (2) for all sensor pairs, identify measurements that are common to the same subset of sensors.

(4) Using one such subset of sensors, compute the sufficient statistic, $\ell_{i_1,i_2,\ldots,i_M}$, using their measurements with Eqs. (2.1)-(2.2), or (2.3)-(2.4) for the Gaussian measurement noise case.

(5) For a desired leakage probability, a threshold for $\ell_{i_1,\ldots,i_M}$ can be chosen using (2.15). Apply the threshold to all $\ell_{i_1,\ldots,i_M}$'s. For those cases that are above the threshold the corresponding measurements are declared uncorrelated. This may again result in some measurements not being correlated at all.

(6) Apply the Hungarian/Munkre type algorithm to process the submatrices resulted from thresholding. This gives the correlation solution.

(7) Let $\ell_{i_1,i_2,\ldots,i_M}$ denote an entry representing a set of correlated measurements. Fix $i_2,\ldots,i_M$, search those $\ell_{i,i_2,\ldots,i_M}$ for all i's that are within a threshold value of $\ell_{i_1,i_2,\ldots,i_M}$. Those entries which are within the threshold define a set of multiple (or redundant) correlations. This step is repeated for all i_j's and all correlations accepted in step (6).

(8) Repeat steps (4)-(7) to process all sensor subsets identified by steps (1)-(3).

The above steps define an algorithm for correlating multiple sensor measurements. The correlation criterion is the minimum sum of weighted distances among measurements from each sensor. For Gaussian measurement noise vectors, the Chi-square statistic is applied to eliminate highly unlikely correlations. A method (step (7)) for accepting multiple correlations for reducing the leakage probability is described.

We note that a multi-dimensional Hungarian/Munkre type of algorithm is not yet available. The row and column elimination method may work well for modest target densities. One may also perform correlation test for all pairs of sensors, in a sequential fashion. The last two approaches are computationally much simpler although they are not optimum.

3. A NUMERICAL EXAMPLE

In this section, we consider an example which illustrates the target handover problem between two sensors. Consider the case of two optical sensors tracking a complex of ballistic targets. The first sensor tracks a subset of targets for 100 seconds then predicts their state vectors 1000 seconds later. The second sensor tracks another subset of targets which partially overlaps that of the first sensor also for 100 seconds. The end of track time of the second sensor is the same as the end of the prediction time of the first sensor. The correlation of estimates from two sensors constitutes a typical handover problem.

Initially, the number of targets tracked by each sensor is equal to twenty with fifteen of them being common to both sensors. The initial spacing of these targets is strictly uniform and very large (with a 5 to 1 target spacing to tracking uncertainty ratio projected to the angle domain) so that incorrect correlations among them are highly unlikely. These targets are moving with nearly the same velocity. The target density is increased by introducing more targets around the original targets where the new targets are randomly distributed with a uniform density over about five percent of the original target spacing and moving with a very small relative velocity. We will call an original target with new targets surrounding it as a cluster. Each sensor therefore tracks twenty clusters where the initial cluster size is one target.

The probability of correct correlation (P_c) and the probability of false correlation (P_f) are defined as follows

$$P_c = \frac{\text{number of targets correctly correlated}}{\text{number of targets}}$$

$$P_f = \frac{\text{number of incorrect correlations}}{\text{total number of correlations declared}}$$

A covariance analysis technique (the Cramer-Rao bound) was applied to obtain the track accuracy using optical sensors, [9]. The simulated state estimate is obtained by corrupting true states with random numbers satisfying the Cramer-Rao covariance bound. A correlation performance using P_c and P_f is obtained with one hundred repetitions on each target.

The P_c and P_f as a function of number of targets in a cluster is shown in Fig. 3.1. we note that a Chi-square threshold of 30 was used for these results. Redundant matches were not allowed. In this case the number of targets is equal to the number of declared correlations, so P_c and P_f sum up to one.

Notice that P_c drops off rapidly as the number of targets in a cluster increases. This is due to the small spacing of targets within a cluster. If one allows for redundant correlations, the P_c can be improved substantially but there will be an increase of P_f. Figure 3.2 shows such a trade-off. We note that the redundant correlation is possible by accepting those targets whose

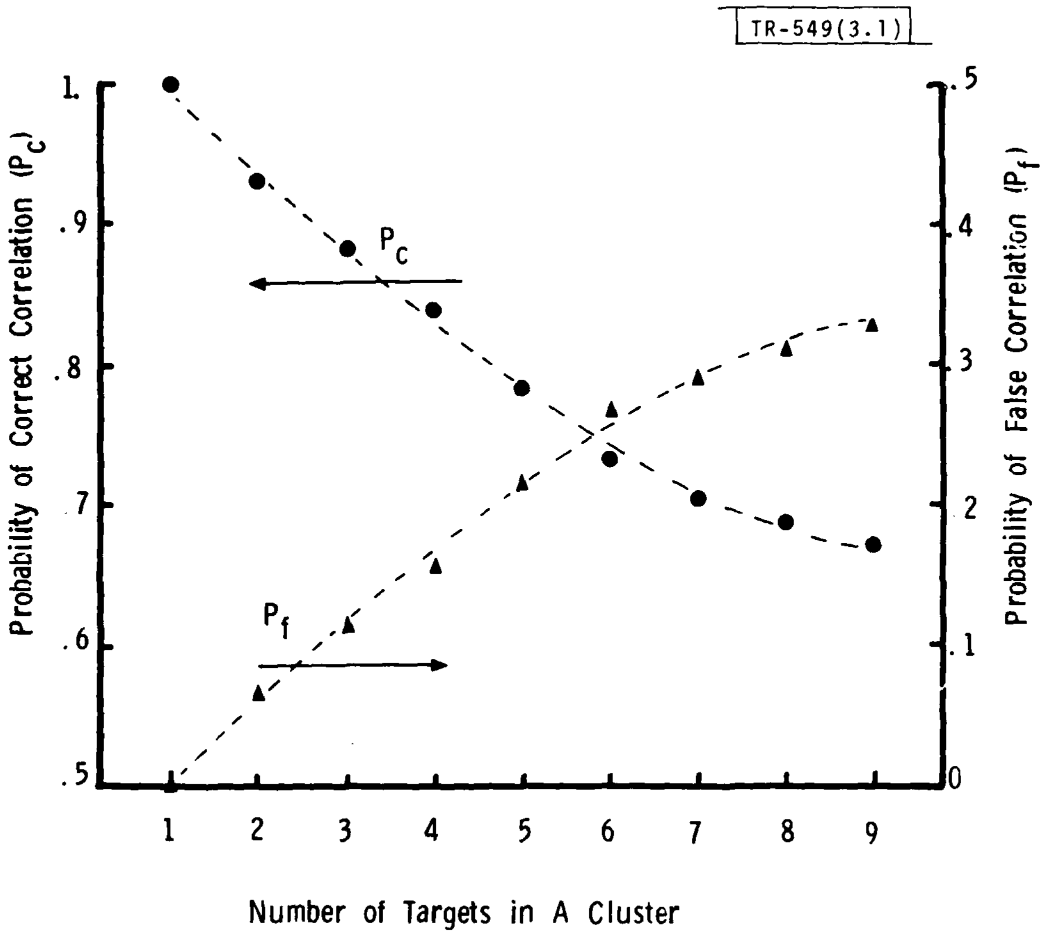

Fig. 3.1. Correct and false correlation probability vs target density, no redundant correlations.

Chi-squares are within a certain range of that of the optimum choice. Results of Fig. 3.2 are obtained with this approach. The dotted line denotes the case of not allowing redundant correlations. Notice that the increase in P_f for maintaining a 90% P_c is rather small.

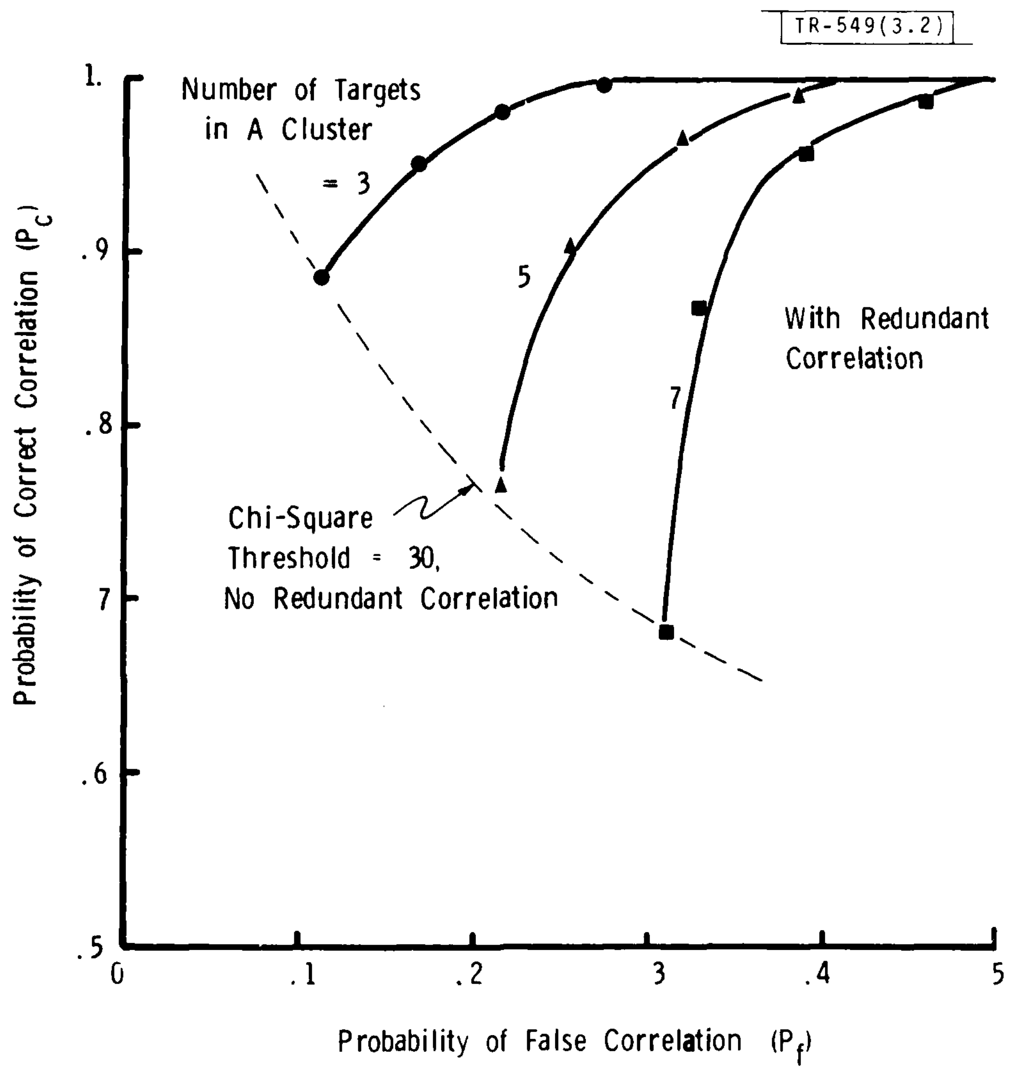

Fig. 3.2. Operating characteristics for sensor-to-sensor correlations with target density as a parameter.

4. SUMMARY

In this report, we have presented an algorithm for correlating measurements of several sensors tracking in a multiple target environment. It is shown that the correlation problem is the same as the assignment problem of operations research with the assignment penalties being equal to the sufficient statistic of the generalized likelihood ratio test. For the case of Gaussian measurement noise, a Chi-square thresholding technique is applied to deal with the problem of high target density, limited sensor resolution, and incomplete overlapping of sensor field of views. An example is given, illustrating the correlation performance and the trade-off between correct correlation and false correlation when redundant correlations are allowed.

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

14 TR-549

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REPORT DOCUMENTATION PAGE

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1. REPORT NUMBER 18 ESD-TR-80-241	2. GOVT ACCESSION NO. AD-A098001	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) 6 Measurement Correlation for Multiple Sensor Tracking in a Dense Target Environment,		5. TYPE OF REPORT & PERIOD COVERED 9 Technical Re[redacted]t
		6. PERFORMING ORG. REPORT NUMBER Technical Report 549
7. AUTHOR(s) 10 Chaw-Bing Chang [redacted] Leonard C. Youens		8. CONTRACT OR GRANT NUMBER(s) 15 F19628-80-C-0002
9. PERFORMING ORGANIZATION NAME AND ADDRESS Lincoln Laboratory, M.I.T. P.O. Box 73 Lexington, MA 02173		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS Program Element Nos. 63304A and 63308A
11. CONTROLLING OFFICE NAME AND ADDRESS Ballistic Missile Defense Program Office Department of the Army 5001 Eisenhower Avenue Alexandria, VA 22333		12. REPORT DATE 11 20 Jan[redacted]81
		13. NUMBER OF PAGES 30
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office) Electronic Systems Division Hanscom AFB Bedford, MA 01731 12 21		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

None

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

multiple sensor tracking
time sequence
sensor measurements
assignment algorithms
measurement correlations

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

In this report, we describe an algorithm for correlating measurements from several sensors. This is a problem area in multiple sensor tracking in a dense target environment. It is shown that the correlation problem is similar to the assignment problem in operation research with assignment penalties being equal to the sufficient statistic of the generalized li[illegible]ood ratio test. An example is given to illustrate the correlation performance for two optical sensors tracking ballistic trajectories.

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